Approaches to the Use of Sensor Data to Improve Classroom Experience

Christian Severin SAUER[1], Tushar Kumar SARKAR[1],
,Samia OUSSENA[1],Thomas ROTH-BERGHOFER[1],
University of West London, Villiers House, Ealing Broadway, London W5 2PA, UK
Tel: ++44 208 231 0250, Email:firstname.lastname@uwl.ac.uk

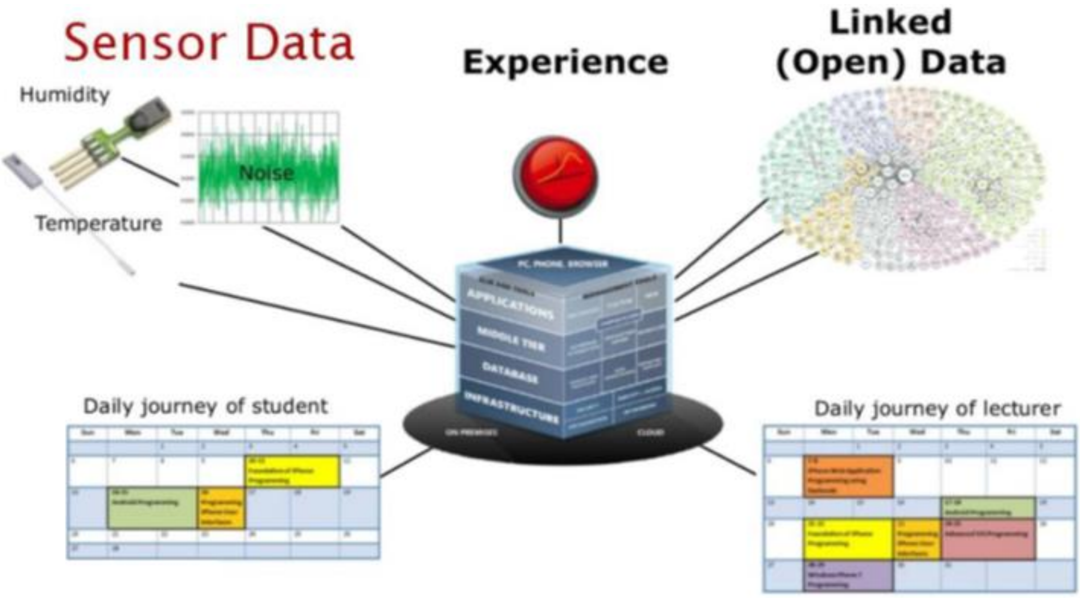
Abstract: Equipping classrooms with inexpensive sensors can enable students and teachers with the opportunity to interact with the classroom in a smart way. In this paper an approach to acquiring contextual data from a classroom environment, using inexpensive sensors, is presented. We present our approach to formalising the usage data. Further we demonstrate how the data was used to model specific room usage situation as cases in a Case-based reasoning (CBR) system. The room usage data was than integrated in a room recommendations system, reasoning on the formalised usage data. We also detail on our on-going work to integrating the systems presented in this paper into our Smart University vision.

1. Introduction

The students and lecturers at our institution, the University of West London (UWL), currently work in a static environment with regard to the allocation of rooms for teaching facilities. The allocation of rooms is currently based on a centrally managed room scheduling system that only takes into account technical necessities such as number of people in a room and for example available computers in a room. Complaints, for example, from students about their studying experience to their lecturers or lecturers' complaints about their teaching environment are currently not very well supported by evidence. Additionally the current system is to slow in case the need appears to change room allocation "on the spot" for example if a laboratory has a technical problem. Furthermore the system is currently not able to "advertise" rooms that became available by unforeseen events such as the cancellation of a lecture.

The approach described in this paper aims to improve the room allocation system at the UWL by the use of contextualised sensor data within an online room recommender system. The proposed system itself is a prototype component of our vision of the Smart University approach.

Within our vision of the Smart University the university is seen as a platform that acquires and delivers foundational data to drive the analysis and improvement of the teaching & learning environment. Sensor-data is joined with linked (open) data (LOD) and formalised teaching knowledge form the source data for the platform. Equipping laboratories and lecture theatres with low cost sensors the platform gathers room usage data and additionally employs single board computers in situ to also process the context of the room usage data, such as retrieving the kind of teaching activity taking place during the sensor recording. The platform employs Case Based Reasoning (CBR) [1] to formalise the captured room usage data in context and re-use it for room recommendations and room allocation planning. Furthermore Smart University links the daily journey of lecturers and students by accessing students and lecturer's online calendars to include the data in personalised room recommendation and allocation [2].



Integration into the smart university vision [2]

The research described in this paper focused on the realisation and evaluation of the sensor units that get data from an array of sensors deployed in a classroom environment. As an implementation of the central data sink, a CBR system was implemented that can retrieve room usage data on specific room situations. The purpose of the CBR system is to act as a room recommender system that recommends the most suitable rooms for students and teachers based on previous recorded data acquired from the sensor units. The room recommender system also incorporates feedback on the suitability of rooms for specific teaching activities, gathered from surveys filled out by students, regarding the most comfortable environment for specific teaching activities such as seminar, lectures or quiet study. The room recommender thus acts as a context-aware system [3], as the different situational contexts of different teaching activities are taken into account.

The rest of this paper is structured as follows: In section 2 we present the objectives of our research. Section 3 then details on the Methodology we employed for our research. In section 4 we then present the technological implementation of the room recommendation systems main reasoning approach CBR and the approaches chosen for the formalisation of the sensor data, combined with the survey data. Section 5 then details on the implementation of two approaches to integrate the sensor units and the room recommendation system into the Smart University platform. The results from experiments with these approaches are then presented in section 6 of the paper and are followed by an argumentation for the business benefits for Higher education institutions that can be derived by the use of our proposed Smart University platform. In the final section 8 we summarise our work and detail on future work on the Smart University platform.

2. Objectives

The objectives of our research were to build a context-aware sensor unit that can acquire contextual data from a classroom environment. The intention of the sensor unit is to gather data, such as noise level, motion, temperature and humidity and in future versions of the system also CO2 levels. The main goal pursued by these measurements is to establish the air quality and overall usefulness of a particular room at any given time, to be able to select rooms most suitable for teaching and thus increase the quality of the teaching and learning experience for bot, the students and the lecturers. We therefore aimed to establish the desirable physical environment with regard to the dimensions of temperature, humidity, noise level and motion level (and in the future CO2 level), for specific teaching activities by surveying the students at UWL. This objective required us to investigate different approaches to the formalisation of the gathered room usage data in the context of the respective teaching activity, including the feedback gathered from the students. To capture this feedback we created and performed surveys with the students on their room usage experiences which we then combined with the sensor data from the sensor units. Based on a suitable approach to the formal representation of the combined sensor and survey data we then aimed to build a CBR knowledge model for the room recommender system. For the purpose of building the CBR knowledge model we had to particularly investigate suitable similarity measures (please see section 3), to enable the knowledge model to compare room usage data. Furthermore we aimed to implement the system as an online system that can display current room usage situations in real time and recommend rooms based on real time online queries. To evaluate our system we had to perform a substantial number of retrieval experiments in the form of getting room recommendations from the system and evaluate the accuracy and quality of these recommendations.

3. Methodology

Based on an initial empirical study [4] of existing work in the utilisation of sensors to monitor room usage situations, context-aware computing, CBR, knowledge formalisation and the design of recommender systems, we designed two approaches to create our own sensor units and integrate them into the Smart University platform.

The implementation of the sensor units and their software followed the Action Research approach [6]. The implementation of the necessary software for the sensor units followed the iterative development approach, starting off with basic prototype software and adding desired features in consecutive implementation cycles.

The design and implementation of the CBR knowledge model and its similarity measures followed the rapid prototyping approach. We employed our own CBR knowledge modelling software myCBR [7] to prototype the knowledge model for the room recommender system.

The evaluation of the built sensor units was performed by quantitative analysis of the sensors data gathered. The accuracy and performance of the room recommender system was evaluated by conducting recommendation experiments and performing qualitative and quantitative analysis on the data gathered form these experiments.

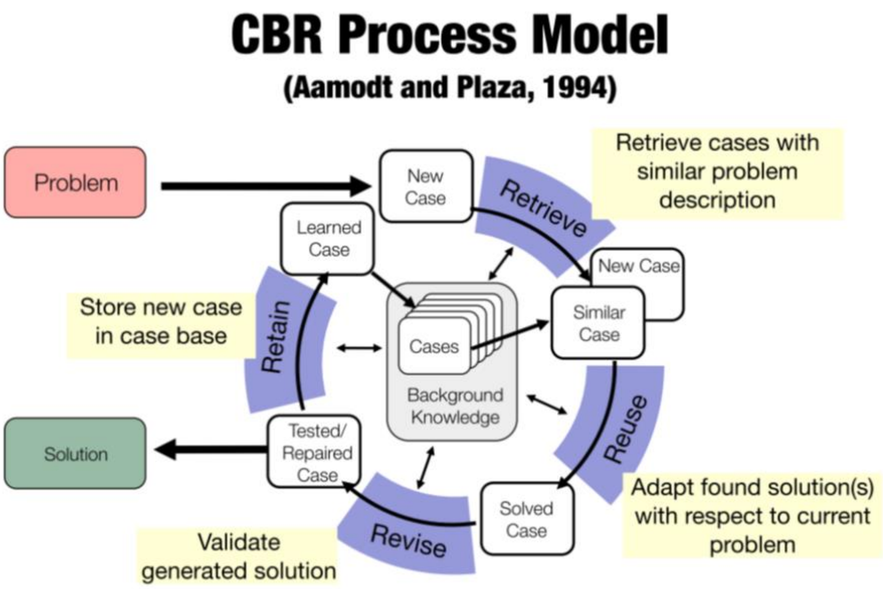
The qualitative feedback data we incorporated in our knowledge model was gathered by surveying students taking part in teaching activities that were monitored by our sensor units and combining the sensor data with the qualitative feedback on the study experience from the students.

4. Technology Description

As mentioned the recommendation of rooms to students or lecturers in our scenario is based on re-using captured room usage data, combined with qualitative feedback from the users of a specific room/teaching activity. The basic idea is to recommend suitable rooms for a specific teaching activities with regard to necessities, such as available computers, number of peoples the room is need to accommodate and also captured feedback how “pleasant” the experience of former students were in a room in the context of a particular teaching activity.

4.1 Case-based room recommendation

The key technology we employed to recommend rooms for specific teaching activities is to “compare” the sensor data and user feedback from former uses of rooms with the current query for a room to recommend the best suited room. To be able to compare recorded room usage experiences with a current query we employ a specific Artificial Intelligence (AI) technique called Case-based reasoning (CBR) [8]. To give a brief introduction to this reasoning technique we introduce its main reasoning process briefly:



The CBR-cycle [1]

A central concept in CBR is the case, where a case consists of a problem description and a solution description. Therefore a case represents recorded knowledge of an encountered problem and the solution that solved said problem. In the context of our work a case’s problem description is describing a specific teaching activity and the necessities of a room, like number of peoples to accommodate and, for example, computers being available. The solution to this problem description is a room that is known to have been suitable and pleasant for past, similar, teaching activities and necessities. Additionally the solution description also contains advice on how to improve the room condition for a specific query, for example by advising to ventilate the room if the air quality is poorly matched. Therefore our system tries to match a query for a room (as a new problem description) witch recorded, pat, queries and re-use the most suitable solution, in our case a room recommendation, to solve the query.

The basic process of the matching of a current problem case to recorded cases to retrieve a best matching case and re-use its solution is described as the CBR-Cycle (please see figure 2). The steps in the CBR cycle are as follows:

1. Retrieve: In this step, one or more cases similar to the current room query are retrieved from the case-base, storing all recorded room usage cases. that are similar to the current problem description from the case base. The matching of the query to the recorded room usage cases is performed by calculating the similarity of the problem descriptions, using similarity measures.

2. Reuse: This step re-uses the solution, or room recommendation, from the retrieved case that is most similar to the current room query. If required, the proposed solution is adapted to fit the current problem [1].
3. Revise: In this step, the proposed solution is tested by evaluating the room recommendation and revised it if necessary.
4. Retain: In the final step of the cycle the applied, successful, room recommendation, together with the room query, is kept as a new case. Therefore the new query and the (possibly adapted) successful room recommendation is retained to be reused to solve a similar problem in the future [9].

4.2 Gathering usage data

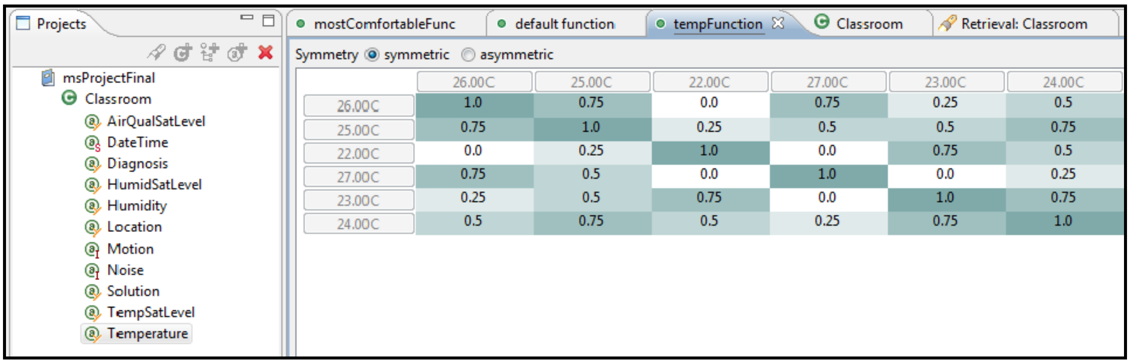
The objectives of the project included the acquisition of contextual data via an array of sensors in a classroom environment, generating knowledge models in myCBR workbench, an open source CBR system prototyping tool, and developing a case base from acquired sensor and survey data to recommend the most suitable physical environment.

We developed two approaches to the gathering of sensor data. The first approach only gathered motion data, using and Infrared (IR) motion detection sensor connected to a low cost single board computer. A second approach we implemented was more sophisticated and used sensors to capture data on temperature, motion, humidity and noise level inside a room. Again these sensors were controlled by a low cost single board computer. Both approaches communicated the sensor data to a central data sink. The first approach employed UHF radio communication mesh networks to communicate the sensor data, while the second approach worked upon existing Wi-Fi networks. The advantage of the radio based approach was the applicability of the sensor networks in areas were no Wi-Fi infrastructure is present. Both approaches employed low cost single board computers to control the sensors, with regard to sensing intervals and to pre-process the raw sensor data captured. This pre-processing basically aimed to derive a contextualise usage situation description for the room, combining the sensor data with other data such as date, time, location and additional data, for example from the online lecture schedule.

The necessary qualitative feedback on particular room usage situations was gathered from student volunteers. These students gave qualitative feedback on their learning experience in selected room/teaching activity constellations. This feedback was then used as a quality measure in the room recommendations to enable the system to recommend rooms that are not only, technically, suitable for a specific teaching activity but also offer a “pleasant” experience.

4.3 Knowledge formalisation

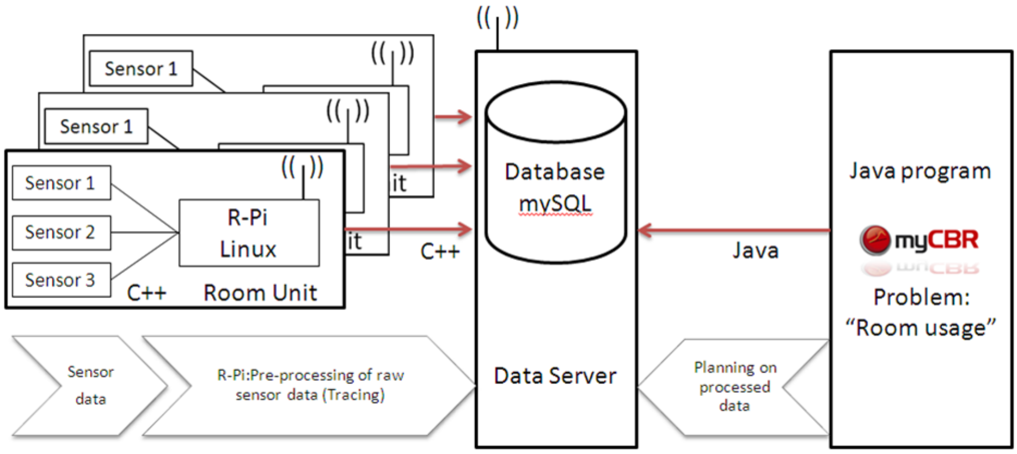
To be able to recommend rooms using a CBR-based recommender system we had to represent the gathered room usage data and the quality feedback from the students in a suitable knowledge model. We employed our own CBR development software, myCBR 3.0 to create the initial knowledge model and refine it, based on retrieval (room recommendation) tests. The basic aspects of the knowledge model we defined were the domain vocabulary, such as the concept room and its attributes and the value ranges of these attributes and the similarity measures needed to compare values of these attributes to calculate their similarity [10]. The calculation of these similarities were distance-based and resulted in a specific value from the normalised interval [0, 1] where 0 stand for totally dissimilar and 1 for identical values. So for example a similarity value of 0.8 still represents a fairly similar pair of values, whilst a similarity of 0.15 describes already quite dissimilar values for an attribute. We additionally modelled a global similarity measure to compute the overall similarity of a query’s problem description to the problem descriptions in all stored room usage cases. We employed mathematical distance functions, comparative tables and taxonomies as similarity measures, please see figure 3 for an example of a comparative table similarity measure.



Comparative table similarity measure for the attribute " room temperature" [2]

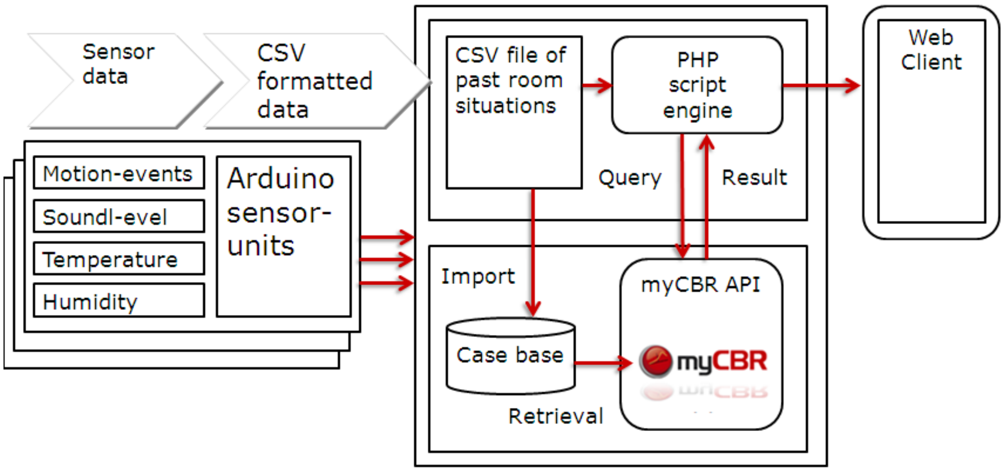
5. Developments

This section describes the design of both systems built to serve as the room recommendation facility within the Smart University approach. The first approach employed Raspberry Pi (R-Pi) computers to handle up to three motion sensor units. The sensor data was pre-processed by the R-Pi computers in that way that based on quantitative analysis an estimate of a room's usage situation was derived. This estimate was than enriched with date, time and location information and formatted in a report in XML that was sent to a general data sink via UHF radio signals. The central data sink was a MySQL database that could be accessed by a myCBR CBR-system embedded in a Java-based recommendation software. This approach was developed up until the stage involving the storage of processed room usage estimates in the central data sink. The actual use of the data for room recommendation was not implemented as we decided to follow a more sophisticated approach, our second approach, before we would start to model the CBR knowledge model. However the sensor units, their estimation of room situations and the communication of these estimates in XML format send of UHF radio worked in a satisfactory way.



Our first approach to sensor data based room recommendation

Based on Insights gained from our first, simplified approach, we developed a more sophisticated approach to the problem of sensor data based room recommendation. This second approach was based on Arduino single board computers [11] that controlled an array of different sensors. The sensor units of our second approach were able to sense a room’s temperature, humidity, noise level and motion events in the room. Also different to our first approach our second approach employed Wi-Fi rather than UHF radio to communicate the room usage estimates. The estimates themselves were encoded into Commas-separated-value (CSV) files. This encoding in csv format allowed for the direct import of the room usage estimates as cases into the case-base of our CBR system. As we were satisfied with the richness of the data we gathered from the sensor units we proceeded to formalise the data into our CBR knowledge model and set up a website to access the room usage data in real time as well as to incorporate our CBR-based room recommendation system.



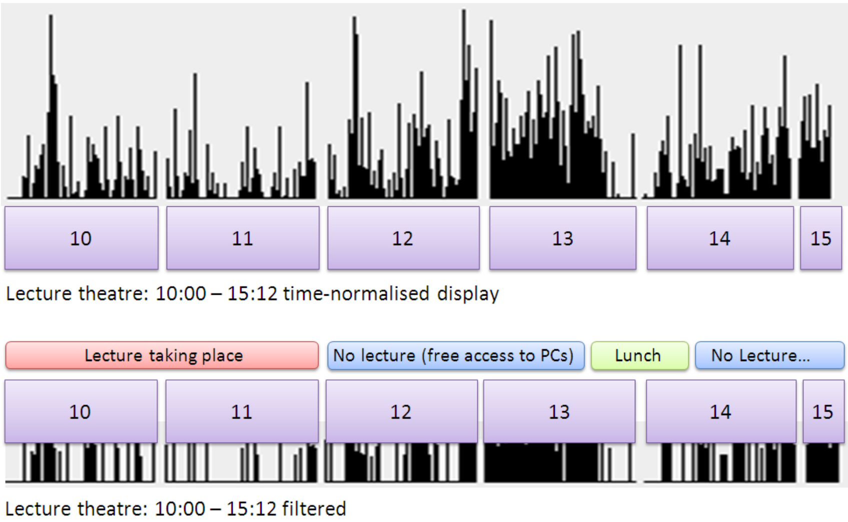
Our second approach to sensor data based room recommendation

It is worth to mention that both our approaches were prototype implementations based on available hardware for experimentation with sensors, such as the Raspberry Pi computers and Arduino boards. In an industrial scale application of our conceptual work the sensor units would, of course, be replaced custom built hardware. Assuming the necessary funding for a pilot system in a higher education institution, the only additional need for our system to be scaled to production level would be a normal, single, database server. Depending on the time needed to create these tailored hardware units we estimate that, as the underlying technologies is already implemented and tested, our approach could reach the market within 8 to 12 months.

6. Results

To evaluate our approaches we performed experiments with both of them. Within our first approach we performed experiments by placing sensor units in 3 classrooms and offices. The sensor units performed satisfactory and the situation estimates for each room were comunicated to the central data sink via radio without interference. However we noticed that in steelframe buildings the radio signal of the sensor units was diminishing quickly and thus the range of the sensor units communication was reduced significantly. We assume that this problem can be solved by the use of the ability of the sensor units to create mesh networks and communicate the room situation estimates of more remote sensor units through this network.

With regard to the data gathered from the sensor units we performed a quantitative analysis on the gathered data. Based on this simple analysis we were able to establish that already one motion sensor with a messauring interval of 1 minute gathered enough data to allow for a reasonably accurate estimate of a rooms usage. We based this estimate on the count of motion events triggered by the sensor per minute, please see figure 6 for an example of the data from one sensor unit.



Initial quantitative analysis of motion events in our first approach

To evaluate our second approach we performed retrieval (recommendation) experiments and analysed the sensor data. An initial important point that we noticed was the data volume. As we stored al contextual data acquired by different sensors in CSV format, so that it can be directly imported into our CBR system. The format allows rapid generation of cases from its records. However, this file format is not the best one to use when data volume becomes massive. If a large number of sensor units are deployed in different locations, a massive number of records are destined to be stored. For efficient handling of this data in a later stage of our system we will therefore employ Hadoop.

With regard to the actual retrieval (recommendation) of rooms we performed retrieval experiments upon a case base that consisted of 2,452 instances of classroom environments. It is worthwhile to mention that this number is not the number of classrooms monitored but rather resulted from the monitoring of several rooms over time. The results from these retrieval experiments were analysed in a qualitative way, mainly in the form of user feedback, were a student or lecturer posted a room query to the system and was asked of his/her estimate of the recommendations accuracy and quality, e.g. if the person agreed that the system recommended a suitable room. A convenient majority of the feedback indicated a satisfactory quality of our systems room recommendations. Furthermore, to determine the most desirable physical environment in a classroom in terms of temperature, humidity and air quality, surveys were conducted at different locations at different times in the University.

7. Conclusions

In this paper we proposed two approaches to the use of sensor data to improve the classroom experience of students in a higher education institution. We justified our work by describing the facts that motivated it. We introduced the conceptual approaches and detailed on the technical implementation of both approaches. We then described the evaluation we performed on both approaches. In conclusion we deem our customer target group for the Smart University approach to consist of medium to large scale teaching organisations. Such organisations could range from private schools to large universities.

Our prototype, built following our second approach, is a product that aims to optimise the daily journey e.g. learning experience of students as well as optimise the daily journey e.g. teaching experience of teachers and lecturers.

As we have stated in the paper the technologies necessary for our approaches are implemented and tested with good results, therefore we assume our approach to be of significant interest for industrial application mainly in the higher education area but not limited to this market as major corporations with larger buildings may also be interested in our approach. However, our initial target market is constituted of medium to large scale teaching organisations in the UK with a preference for higher education organisations. We expect our market to grow due to: Growth in the education sector overall, a growing need for teaching organisations to optimise and their performance and use of resources and a growing need to offer performance to (learning) customers.

For our immediate future work on the prototype system we plan to add more sensors (e.g. CO2 detection sensor, light detection sensor). We also want to re-implement the UHF radio communication from our first approach to enable our prototype system to be independent of existing Wi-Fi infrastructures. We also plan to enhance the design of the prototype's web client and add a specific mobile application to the system. Finally we are investigating the use of the X10 protocol to control devices (e.g. heating) in a classroom based on the room usage estimates established by our prototype system.

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